Received: 26 April 2021 | Revised: 4 January 2022 | Accepted: 22 February 2022

DOI: 10.1002/hec.4499

SHORT RESEARCH ARTICLE

Health Economics Letters

Health Economics WILEY

Throwing caution to the wind: How hurricanes affect COVID-19 spread

Marlon Tracey | **Alicia Plemmons** | **Ariel Belasen**

Department of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, Illinois, USA

Correspondence
Alicia Plemmons, Department of Economics and Finance, Southern Illinois University Edwardsville, 125 Peck Services Rd. Alumni Hall #3132, Edwardsville, IL 62026, USA.
Email: amplemmons@gmail.com

Abstract

This study exploits the pathway of Hurricane Laura to assess its impact on the spread of COVID-19. Using US hospital data on confirmed and suspected adult COVID-19 cases, we find average daily cases per week rose by more than 12% primarily in tropical storm-affected counties in subsequent weeks. We suspect the key mechanisms involve constraints on social distancing for two reasons. First, there is significant evidence of storm-induced mobility. Second, lower income areas endured higher growth in hospital cases during the post-hurricane period. These findings provide crucial insights for policy-makers when designing natural disaster protocols to adjust for potential respiratory viral illnesses.

KEYWORDS
COVID-19, hurricanes, mobility, pandemic

JEL CLASSIFICATION
I14, I18, Q54

1 | INTRODUCTION

Early summer 2020, researchers warned the surging COVID-19 Pandemic and looming hurricane season could cause dire domino health effects for coastal states (Shultz, Fugate, & Galea, 2020; Shultz, Kossin, et al., 2020). Although mitigation policies such as social distancing or stay-at-home orders are effective against the pandemic (Courtemanche et al., 2020), they likely have limited or non-existent provisions for natural disaster preparedness. As a storm forces people, including the infected, to become more mobile, mass transit, communal shelters, and other destinations for evacuees grow in density, potentially incubating new COVID-19 cases (Price et al., 2020). Implications are particularly stark for the poor who have a lower capacity to social distance (Weill et al., 2020). Several studies have shown COVID-19 to spread in similar crowded public spaces owing to, for example, a presidential primary election (Cotti et al., 2021), a motorcycle rally (Dave et al., 2021), sporting events (Ahammer et al., 2020), and student holiday travel (Mangrum & Niekamp, 2020). Still, the extent naturally occurring events such as hurricanes contribute to further spread is unknown.

We therefore exploit Hurricane Laura's unexpected growth in the Gulf Coast to estimate its effect on COVID-19 infections using US hospital-level data. In 2020, amid the most active Atlantic Hurricane Season on record, Laura was the strongest hurricane to hit the United States.[1] At Category 4, its maximum wind speed was 150 mph upon landfall in Louisiana early August 27, and its tropical storm-force winds (39–73 mph) extended to parts of Arkansas, Mississippi, and Texas (Pasch et al., 2021). Later that day, Laura weakened to a tropical depression over Arkansas. Governors of all four states declared states of emergency 1–6 days before landfall, which recommended flood-prone area evacuations, initiated emergency shelter protocols, and allowed access to disaster emergency funds. That same week, those states averaged COVID-19 hospitalizations of nearly 20 per 100,000 people and positivity rates of about 12%, with over 80% of

 © 2022 John Wiley & Sons Ltd.

their counties experiencing substantial/high transmissions.[2] This was before vaccines were available and after state mitigation policies generally ended, except for mask mandates in public spaces (see Raifman et al., 2020). Given this setting, we analyze differential trends in mobility and hospitalized/ICU COVID-19 cases between storm-affected and unaffected counties over 6 weeks (August 7 to September 17), allowing for heterogeneity based on wind-force and income levels.

2 | DATA

We examine 405 hospital facilities in 199 counties across Arkansas, Louisiana, Mississippi, and Texas. We focus on the Eastern and Upper Gulf Coast counties of Texas, which are hurricane-prone and more closely resemble Arkansas and Louisiana in demographic makeup. The National Oceanic and Atmospheric Administration provides the path of Hurricane Laura's eye and surface wind field data defined at three wind speed thresholds: 39, 59, and 74 mph. Figure 1 shows Laura's path and wind field with at least 39 mph winds. It traveled northwards along western Louisiana and weakened to a tropical storm before crossing into Arkansas. Hospitals are considered affected by Laura if they are located in counties within the wind field; otherwise, they are unaffected. Our sample comprises roughly one-half of hospitals in 93 storm-affected counties.

Most hospitals must report daily COVID-19 capacity data to the U.S. Department of Health and Human Services (HHS) for Federal response planning.[3] Starting July 31, 2020, HHS released weekly (Friday to Thursday) counts of adults currently hospitalized or in ICU with confirmed or suspected COVID-19, as well as data on staffed beds.[4] But it redacted non-zero cases fewer than four for privacy concerns—we address this econometrically in Section 3. Since reporting days per week vary from 1 to 7, we compute average daily cases per week. Focusing on hospital cases is important as they are less discretionary, given preferential access to testing, and federally required to be reported.[5] Our event-study analysis of this data spans 3 weeks prior to Laura's landfall on August 27, since hospitalization data are unavailable from July 27 to August 6 for Louisiana.[6] The post-event period ends September 17 to avoid confounding with other proximate hurricanes (e.g., Sally on September 16). We only analyze hospitals with data pre- and post-Hurricane Laura.

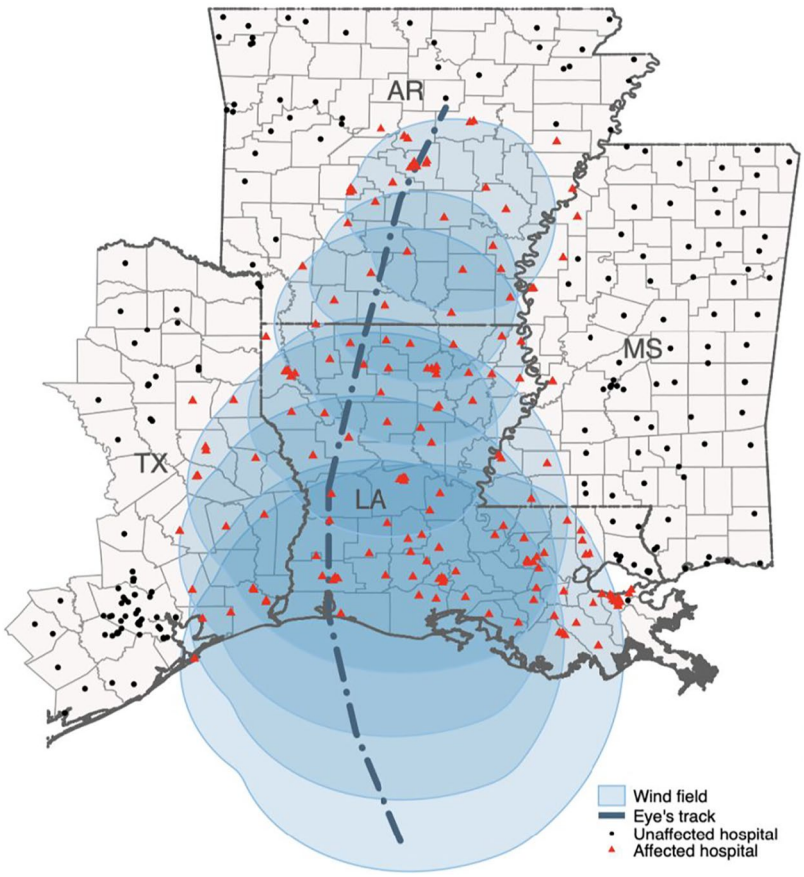

FIGURE 1 Hurricane Laura's path and wind field comprising at least 39 mph winds [Colour figure can be viewed at wileyonlinelibrary.com]

Our analyses rest on four additional data sources. Given no changes in state mitigation and reopening polices during our study period (see Raifman et al., 2020), we use state-level testing data from The COVID Tracking Project (2021) to gauge states' responses/attitudes to the pandemic based on tests availability and outbreak severity. We also rely on anonymized smartphone location data, from SafeGraph and PlaceIQ, to assess differences in mobility between storm-affected and unaffected counties. The two companies track tens of millions of smartphones via GPS pings daily. We use SafeGraph's census-block-group-level counts of devices completely at home and aggregate it to the county level, as a percent of all devices in a county. Using PlaceIQ data, Couture et al. (2021) provides two indices: (i) the average number of devices encountered at commercial venues by devices in a given county on the same day (i.e., device exposure), and (ii) the share of devices in a county that were in any other county in the last 2 weeks (i.e., location exposure). For each measure, we compute a county's average daily mobility level per week (as per HHS reporting period). These data are commonly used to study social distancing behavior (e.g., Dave et al., 2021; Weill et al., 2020). Finally, to check for effect heterogeneity across income groups, we define low- and high-income thresholds as the first and third quartiles of the 2019 county median household incomes in our study states (i.e., $39,840 and $53,423), using American Community Survey 5-year data.[7]

3 | METHOD

We employ the following event-study framework to estimate Hurricane Laura's impact on a community's average daily adult COVID-19 cases that require a hospital (y^*_{icst}).

$$\log\{\mathbb{E}(y^*_{icst})\} = \gamma_c + \eta_t + \psi' x_{icst} + \sum_{j=-2,\, j\neq 0}^{3} \beta_j \cdot T_j \cdot h_c \tag{1}$$

We measure y^*_{icst} using HHS-reported data on y_{icst}, that is, the average of daily cases in week t admitted to hospital i, located in county c in state s. However, we only know $y_{icst} \leq 3$ when weekly case counts are between 0 and 4 due to HHS suppression. Moreover, $y_{icst} = 0$ may not mean a hospital service area had no moderate-to-severe cases. It may only indicate few such cases existed, but they sought care elsewhere (e.g., urgent care centers) or held out at home (e.g., deterred by medical costs, bed capacity, hurricane ruins). Thus, when hospitals report under four cases in a week (i.e., censored observations), we assume $y^*_{icst} \leq 3$; otherwise, we set $y^*_{icst} = y_{icst}$.[8] Table 1 shows pre-hurricane weekly hospitalized and ICU cases less than four occurred at a rate of 31%–35% and about 50%, respectively. When facilities had at least 4 cases in a week, they averaged about 16–18 hospitalized and 9–10 ICU cases daily.

Equation (1) adjusts for static cross-county differences and secular trends in outcomes using county and week fixed effects (γ_c and η_t), respectively.[9] Via x_{icst}, we also control for log number of staffed hospital beds and log number of tests

TABLE 1 Hospital-level variables at baseline (August 7–27)

	Baseline sample		Mean by status	
	Mean	S.D.	Affected	Unaffected
Hospitalized cases				
Weekly count (C) < 4	0.350	0.477	0.446	0.272***
Avg. daily (C) | weekly count ≥ 4	16.18	23.43	14.73	17.09
Weekly count (S/C) < 4	0.308	0.462	0.394	0.237***
Avg. daily (S/C) | weekly count ≥ 4	17.80	26.69	15.53	19.29
ICU cases				
Weekly count (C) < 4	0.503	0.500	0.558	0.449**
Avg. daily (C) | weekly count ≥ 4	8.980	11.55	7.321	10.31*
Weekly count (S/C) < 4	0.495	0.500	0.545	0.445**
Avg. daily (S/C) | weekly count ≥ 4	9.521	12.21	7.465	11.21**
Total staffed beds	120.7	188.1	97.57	141.8
Number of hospitals	405		192	213

Note: C indicates confirmed cases only and S/C indicates suspected or confirmed cases. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

conducted in state s in week t. Finally, the indicator h_c equals to 1 if Laura impacted county c, and 0 otherwise. Interacting it with week dummy T_j allows for estimating β_j, the effect of Laura when j weeks away from the week of landfall.

Given y_{icst} is non-negative, continuous, and right-skewed with mode at zero, we let y^*_{icst} have an exponential density $f\left(y^*_{icst}\right) = \mu^{-1}e^{-y^*_{icst}/\mu}$, where $\mu = \mathbb{E}\left(y^*_{icst}\right)$. We then estimate a censored exponential regression by maximizing this log-likelihood: $\log L = \sum_{i,t\notin C} \log f(y_{icst}) + \sum_{i,t\in C} \log F(3)$, where C is the set of censored observations and $F(\cdot)$ is the exponential cumulative distribution function. Estimates of β_j, when $j < 0$, partially test that affected and unaffected counties share parallel trends in outcomes. But when $j > 0$, they provide post-hurricane weekly effects. We also estimate two variants of Equation (1), where (i) we replace the left-hand side with $\mathbb{E}$(mobility), take x_{cst} as log (tests), and apply ordinary lease squares; or (ii) we interact $T_j \cdot h_c$ with income or wind speed levels.[10]

4 | RESULTS

Table 2 presents estimated marginal effects (β_j) of Hurricane Laura on log of expected daily cases requiring a hospital at various times from week of landfall. Prior to landfall, differences in trends are small and insignificant for either confirmed-only or suspected/confirmed COVID-19 cases. A week after landfall, however, column 1 shows higher average daily confirmed hospitalized cases by 12.6% ($e^{0.119} - 1$), with larger effects 2–3 weeks later (17%–26%). We find similar results for suspected/confirmed cases (column 3). One might argue the use of hospital facilities increased due to sheltering needs by asymptomatic or mildly symptomatic people who would have otherwise stayed home. But such cases would not require ICU interventions. Columns 2 and 4 show the trend for ICU cases is similar to hospitalized cases, with notably larger effects within 2–3 weeks (i.e., over 35%). These estimates may be lower bounds since Laura arrived while states had mask mandates, which tend to slow case growth (Chernozhukov et al., 2021; Karaivanov et al., 2021). Although our estimates reflect growth in hospital cases, they are comparable in magnitude to Dave et al.'s (2021) finding that the Sturgis Motorcycle Rally in Meade County, South Dakota raised COVID-19 cases by at least 31% in the county and its neighbors or by at least 12% in the state.

A potentially key reason Laura spread COVID-19 is that it induced mobility, especially where it is harder to mitigate the spread. To explore this, Table 3 provides marginal effects of Laura on three mobility measures. Within a week of Laura's arrival, for affected counties, the share of people staying home fell by 2.1 pp, and movements to crowded areas (device exposure) and other counties (location exposure) rose by 10.4% and 0.7 pp, consistent with late evacuations,

TABLE 2 Hurricane Laura's effect on hospital COVID-19 cases

	Confirmed only		Suspected/confirmed	
	Hospitalized	**ICU**	**Hospitalized**	**ICU**
Time to week of landfall				
2 weeks	0.005	−0.023	−0.014	−0.046
	(0.070)	(0.099)	(0.066)	(0.098)
1 week	0.027	0.006	0.006	0.000
	(0.053)	(0.077)	(0.053)	(0.077)
$\chi^2(2)$ p-value	0.852	0.838	0.933	0.678
Time since week of landfall				
1 week	0.119**	0.174***	0.083	0.163***
	(0.060)	(0.058)	(0.060)	(0.059)
2 weeks	0.161**	0.311***	0.161**	0.337***
	(0.078)	(0.075)	(0.077)	(0.075)
3 weeks	0.234**	0.335***	0.175**	0.348***
	(0.092)	(0.093)	(0.085)	(0.088)
Observations	2258	2224	2268	2225

Note: Coefficients are weekly marginal effects (β_j) from Equation (1), which adjust for county and week fixed effects, as well as hospital and testing capacities. All coefficients are expressed relative to the week of landfall. They are interpreted as percentage change when transformed to $(e^{\beta_j} - 1) \times 100$. Standard errors in parentheses are clustered at the county level. Pre-trend χ^2-test is a joint test for any pre-hurricane differential trends in outcomes. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3 Hurricane Laura's effect on mobility

	Completely at home	Device exposure	Location exposure
Time to week of landfall			
2 weeks	−0.087	−0.020	−0.297
	(0.308)	(0.020)	(0.182)
1 week	−0.082	−0.029	−0.288
	(0.309)	(0.020)	(0.182)
F-test *p*-value	0.860	0.335	0.181
Time since week of landfall			
1 week	−2.089***	0.099***	0.737***
	(0.319)	(0.020)	(0.189)
2 weeks	−1.441***	0.057***	0.203
	(0.309)	(0.020)	(0.183)
3 weeks	−1.518***	0.052***	0.059
	(0.312)	(0.020)	(0.185)
Observations	1194	912	912

Note: Coefficients are weekly marginal effects on three mobility measures, estimated by OLS and expressed relative to the week of landfall. They are adjusted for county and week fixed effects, as well as state testing capacity. Mobility is measured using SafeGraph's percent of devices remaining completely at home and Couture et al.'s (2021) indices quantifying exposure of devices to each other at commercial venues (device exposure, expressed in log units) and the percent of a county moving to other counties (location exposure). Standard errors in parentheses are clustered at the county level. Pre-trend *F*-test is a joint test for any pre-hurricane differential trends in outcomes. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

returns, rescues, and recovery efforts. Analyzing mobility effects by wind speed and income level provides greater insight into the mechanism. Figure 2 (Top) shows counties affected by tropical storm-force winds (39–73 mph) spiked in device (crowd) exposure post-landfall. Meanwhile, people from hurricane-affected counties (74+ mph) primarily fled their homes for less-affected counties. Conceivably, evacuees, who shed the virus or are exposed to it, are a major source of COVID-19 spread to nearby counties (Price et al., 2020). In fact, Table 4 (Panel 1) reports higher growth in daily hospital cases after landfall in areas affected by tropical storm-force winds, particularly when 59–73 mph (by at least 22.3%); and no significant impact in hurricane-affected areas.

When we compare mobility effects across income groups (Figure 2, Bottom), the increase in pre-hurricane mobility is somewhat larger for lower income counties, but all experienced a similar surge after landfall. We know these mobility data do not reveal the extent travelers took COVID-mitigating steps and thus their specific risk of catching or spreading the virus. Given the same mobility response, however, we expect travelers from high-income areas to better social distance (e.g., avoid public transit and foot traffic, or isolate at home) than low-income ones. Thus, if mobility under constrained social distancing is a mechanism for storm-induced COVID-19 spread, then the effect should be more pronounced in lower income areas. Table 4 (Panel 2) provides income-group-specific effects of Hurricane Laura on hospital cases. Specifically, we observe at least a 28% increase in daily hospital cases for low-income counties, and smaller magnitudes for higher income ones. These results support our expected mechanism, and reveal important distributional consequences of a dual emergency.

5 | CONCLUSION

Hurricane Laura was the strongest natural event in the United States since the onset of the COVID-19 pandemic in early 2020, providing a unique opportunity to analyze their interaction. We show Laura contributed to COVID-19 spread by increasing adult hospital cases in storm-affected counties of Arkansas, Louisiana, Mississippi, and Texas, mainly the low-income areas. Our results suggest a possible mechanism: disaster mitigation efforts increased mobility in counties with limited capacity to social distance. As more coronavirus variants appear and climate change extends hurricane seasons, our findings reveal a need to redesign evacuation/sheltering plans to make compatible with infectious disease protocols. This may be warranted even with vaccine availability given the potential for breakthrough infections, waning vaccine efficacy, and the lower vaccine take-up in coastal states.

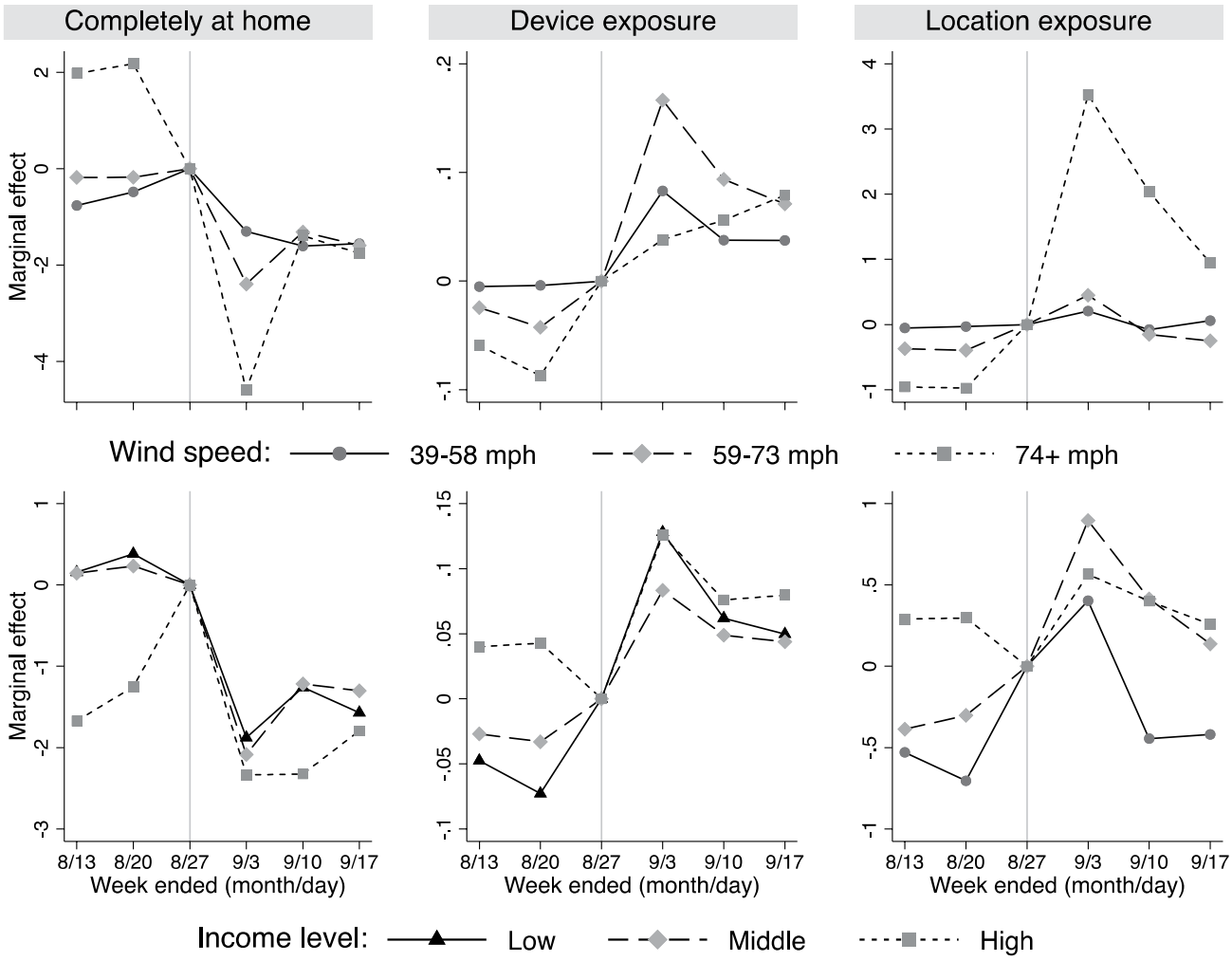

FIGURE 2 Event-study estimates of differences in average mobility between affected and unaffected counties before and after Hurricane Laura's landfall on August 27, by wind speed and income level. They are adjusted for county and week fixed effects and state testing capacity. Estimates are expressed relative to the week of landfall. Mobility is measured using SafeGraph's percent of devices remaining completely at home and Couture et al.'s (2021) indices quantifying exposure of devices to each other at commercial venues (device exposure, expressed in log units) and the percent of a county moving to other counties (location exposure)

TABLE 4 Heterogeneity in average post-hurricane effects

	Confirmed only		Suspected/confirmed	
	Hospitalized	**ICU**	**Hospitalized**	**ICU**
1. Max wind speed				
39–58 mph	0.147*	0.285***	0.106	0.282***
	(0.078)	(0.076)	(0.072)	(0.078)
59–73 mph	0.243**	0.376***	0.201*	0.415***
	(0.111)	(0.098)	(0.106)	(0.088)
74+ mph	0.119	0.055	0.120	0.041
	(0.100)	(0.120)	(0.091)	(0.110)
χ^2 (6) p-value	0.820	0.231	0.914	0.270
2. Median income				
Low	0.248**	0.434***	0.261**	0.456***
	(0.103)	(0.100)	(0.111)	(0.106)
Middle	0.164**	0.252***	0.121*	0.248***
	(0.077)	(0.082)	(0.072)	(0.079)
High	0.092	0.177	0.034	0.204*
	(0.103)	(0.108)	(0.094)	(0.119)
$\chi^2(6)$ p-value	0.786	0.529	0.946	0.454
Observations	2258	2224	2268	2225

Note: Income thresholds are $39,840 (lower quartile) and $53,423 (upper quartile). Coefficients are averages of the post-hurricane weekly marginal effects for each level of wind speed or income, adjusting for county and week fixed effects, as well as hospital and testing capacities. All coefficients expressed relative to the week of landfall. They are interpreted as percentage change when transformed to $(e^{\beta_j} - 1) \times 100$. Standard errors in parentheses are clustered at the county level. Pre-trend χ^2-test is a joint test for any pre-hurricane differential trends in outcomes by wind speed or income level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

CONFLICT OF INTEREST

The authors are responsible for disclosing all financial and personal relationships between themselves and others that might bias their work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from SafeGraph. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at https://www.safegraph.com/academics with the permission of SafeGraph.

ORCID

Marlon Tracey https://orcid.org/0000-0001-6037-2832
Alicia Plemmons https://orcid.org/0000-0002-1573-4686

ENDNOTES

[1] The season featured 30 named storms, with 14 becoming hurricanes and a record-breaking 11 making landfall in the United States (National Oceanic and Atmospheric Administration, 2020). In Louisiana and Texas, Laura led to 41 deaths, 10,000 demolished homes, and about 568,000 power outages. Damages amounted to $19B (Pasch et al., 2021).

[2] Values based on The COVID Tracking Project (2021) and The New York Times (2021) data. The Centers for Disease Control and Prevention (CDC) defines substantial or high transmission as at least 50 weekly new cases per 100,000 persons or at least an 8% positivity rate.

[3] Either hospitals report to HHS via an online platform or state health departments directly report on their behalf. Hospitals can update past reporting, given improved information. The data release omits US Department of Veteran Affairs, Defense Health Agency, Indian Health Service, psychiatric and rehabilitation hospitals. See HHS (2021) for other details.

[4] Sample hospitals have on average 120 total staffed beds (SD = 188), which varies over time due to staff availability.

[5] General case counts, however, may be an artifact of the hurricane impacting people's decision to get tested, tests availability, and reporting procedures. Still, using county data from The New York Times (2021), we compute weekly growth in new cases (like Chernozhukov et al., 2021) as the left-hand side of Equation (1), where x is weekly growth in new tests at the state level—county-level data unavailable. Estimates 1–3 weeks post-hurricane are 13%, 20%, and −5% respectively, but are imprecise (with $p > 0.2$), potentially reflecting storm-induced noisy case data.

[6] Also, some Louisiana hospitals' average daily suspected/confirmed COVID-19 hospitalizations are lower than confirmed-only cases by one or more. Not knowing why, we assign those cases to missing. Including them, however, does not qualitatively change our findings, albeit estimates are somewhat bigger and more significant.

[7] Bottom and top quintiles produce similar results.

[8] Our basic estimates are slightly larger if we assume $y^*_{icst} \leq \tau$, for $\tau = 0.5, 1, 2$.

[9] We considered state-by-week fixed effects but, as Figure 1 shows, nearly all our sample counties in Louisiana were affected by Laura, thus fixed effects left little useable variation in h_c that is contributed by Louisiana.

[10] Another possibility is effect heterogeneity based on whether pre-hurricane COVID-19 county transmission is substantial/high (as defined by the CDC). But nearly all sample counties (190 of 199) had substantial/high transmissions. Thus, our conclusions may only generalize to counties with flourishing COVID rates.

REFERENCES

Ahammer, A., Halla, M., & Lackner, M. (2020). Mass gatherings contributed to early COVID-19 mortality: Evidence from US sports. *Covid Economics: Vetted and Real-Time Papers*, *30*, 40–62.

Chernozhukov, V., Kasahara, H., & Schrimpf, P. (2021). Causal impact of masks, policies, behavior on early COVID-19 pandemic in the US. *Journal of Econometrics*, *220*(1), 23–62.

Cotti, C., Engelhardt, B., Foster, J., Nesson, E., & Niekamp, P. (2021). The relationship between in-person voting and COVID-19: Evidence from the Wisconsin primary. *Contemporary Economic Policy*, *39*(4), 760–777.

Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong social distancing measures in the United States reduced the COVID-19 growth rate. *Health Affairs*, *39*(7), 1237–1246.

Couture, V., Dingel, J. I., Green, A., Handbury, J., & Williams, K. R. (2021). JUE Insight: Measuring movement and social contact with smartphone data: A real-time application to COVID-19. *Journal of Urban Economics*, 103328. https://doi.org/10.1016/j.jue.2021.103328

Dave, D., McNichols, D., & Sabia, J. J. (2021). The contagion externality of a superspreading event: The Sturgis Motorcycle Rally and COVID-19. *Southern Economic Journal*, *87*(3), 769–807.

Karaivanov, A., Lu, S. E., Shigeoka, H., Chen, C., & Pamplona, S. (2021). Face masks, public policies and slowing the spread of COVID-19: Evidence from Canada. *Journal of Health Economics*, *78*, 102475. https://doi.org/10.1016/j.jhealeco.2021.102475

Mangrum, D., & Niekamp, P. (2020). JUE Insight: College student travel contributed to local COVID-19 spread. *Journal of Urban Economics*. https://doi.org/10.1016/j.jue.2020.103311

National Oceanic and Atmospheric Administration. (2020, November 24). *Record-breaking Atlantic hurricane season draws to an end*. Retrieved October 6, 2021, from https://www.noaa.gov/media-release/record-breaking-atlantic-hurricane-season-draws-to-end

Pasch, R. J., Berg, R., Roberts, D. P., & Papin, P. P. (2021, May 26). *Tropical cyclone report Hurricane Laura (AL 132020) 20-29 August 2020*. National Hurricane Center. Retrieved October 6, 2021, from https://www.nhc.noaa.gov/data/tcr/AL132020_Laura.pdf

Price, C. C., Klima, K., Propp, A. M., & Colbert-Kelly, S. (2020). *A model of the spread of the COVID-19 pandemic during a hurricane in Virginia [Research report]*. RAND Corporation.

Raifman, J., Nocka, K., Jones, D., Bor, J., Lipson, S., Jay, J., & Chan, P. (2020). *COVID-19 US state policy database*. Retrieved August 27, 2021, from www.statepolicies.com/data

Shultz, J. M., Fugate, C., & Galea, S. (2020). Cascading risks of COVID-19 resurgence during an active 2020 Atlantic hurricane season. *JAMA*, *324*(10), 935–936.

Shultz, J. M., Kossin, J. P., Hertelendy, A., Burkle, F., Fugate, C., Sherman, R., Berg, K., Maggioni, A., Espinel, Z., Sands, D. E., LaRocque, R. C., Salas, R. N., & Galea, S. (2020). Mitigating the twin threats of climate-driven Atlantic hurricanes and COVID-19 transmission. *Disaster Medicine and Public Health Preparedness*, *14*(4), 494–503.

The COVID Tracking Project. (2021). Retrieved September 22, 2021, from https://covidtracking.com/data

The New York Times. (2021). *Coronavirus (Covid-19) data in the United States*. Retrieved March 17, 2021, from https://github.com/nytimes/covid-19-data

U.S. Department of Health & Human Services. (2021). *COVID-19 reported patient impact and hospital capacity by facility*. Retrieved December 28, 2021, from https://healthdata.gov

Weill, J. A., Stigler, M., Deschenes, O., & Springborn, M. R. (2020). Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proceedings of the National Academy of Sciences*, *117*(33), 19658–19660.

How to cite this article: Tracey, M., Plemmons, A., & Belasen, A. (2022). Throwing caution to the wind: How hurricanes affect COVID-19 spread. *Health Economics*, *31*(6), 1258–1265. https://doi.org/10.1002/hec.4499